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# Computational Modeling of Hippocampus to Store and Retrieve Patterns using Spiking Neural Network

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**Abstract:** *In this research article, a computational model is proposed for DG and CA3 region of the hippocampus. Model is designed to store overlapped patterns, and to retrieve a complete pattern from a cue. In Proposed model, DG and CA3 region of the hippocampus is designed as pattern separator and as pattern storage respectively, where firing-rate based pattern separator is used. Here, DG and CA3 is combinedly described as two sequential associative networks. First network is used as a pattern separator and other one is used as a memory for storage of pattern to perform pattern completion from the incomplete pattern. Whole model is designed using Spiking neural network which makes it more realistic in nature. Model is deployed to store the grid patterns of black white blocks, and also recalling has been done successfully. Also, the architecture of proposed model follows the major phenomena of hippocampus like sparse connectivity and activation in DG.*

**Keywords:** Hippocampus modeling, Spiking Neural Network, Recalling.

## Introduction

Hippocampus is a brain region present in the medial temporal lobe of the brain [1,2,4]. It is widely believed by the scientific community that the hippocampus is a site responsible for the episodic memory and its recalling [1,2,4]. It can store the different events like birthday party of friend, own marriage ceremony etc, where some events can be so much similar like parking the car at office today and yesterday. These similar events require some operation by the hippocampus which can make these similar events different, which we call pattern separation. This is why hippocampus works as a pattern separator. Hippocampus is also a long-term storage site [3,5], where it stores the memory in the form of synapses by making associations between the coactive neurons. The whole stored event can be recall on giving the incomplete event related information (cue), for example: place where event is occur, this is a pattern completion operation which the hippocampus performs.

Hippocampus just requires single exposition to learn a pattern [1,4], but it can be weakened by exposure to similar events. The memories stored in Hippocampus always tagged with some spatial and temporal context. In one of the research [1], it is said that the firing rate of DG neurons decides the neuron in CA3 region to store the input pattern. We used this concept of firing rate to separate the patterns in proposed model.

Hippocampus is described as a sequential circuit consists of DG, CA3, CA1, Subiculum. Where DG takes the input from the Entorhinal cortex. It is found in various research that the DG separate the two similar patterns by reducing the overlapping between the similar patterns or the overlapped patterns. By the help of this functionality of DG, hippocampus stores the similar patterns differently. CA3 region of the hippocampus comes after the DG in sequential loop, it takes input from the DG. CA3 is mainly described as an associative network which stores the patterns processed by the DG.CA3 is having the recurrent loops which is used to make the associations with other neurons to store the patterns in the form of synapse (associative memory)[4].

The aim of our research is to model the DG and CA3 region of the hippocampus using spiking neural network to store and retrieve the overlapped patterns.

We designed DG as a pattern separator, and CA3 as a pattern storage site by the help of two sequential associative networks. Our model is follows the sparse activation property of DG, sparse connectivity between the DG and CA3, also follows the ratio of the required number of neurons between the DG and EC (explained in below section).

## Literaure Survey

In literature survey, we covered the structural details of Hippocampus, and its functionality. Also, we covered the spiking neural network, and other previous computational models of hippocampus.

Structure of Hippocampus:

It is a sequential circuit (shown in figure1) consists of DG, CA3, CA1, subiculum. It takes input from the Entorhinal through DG. DG is having granule cells which is having five times more neurons comparatively to the number of EC neurons. Where each granule cell takes input from the many EC cells and sends output to the CA3 though the mossy cells. This DG neurons show the sparse activity for each pattern, about 2-4% neuron only activates at a time [11].

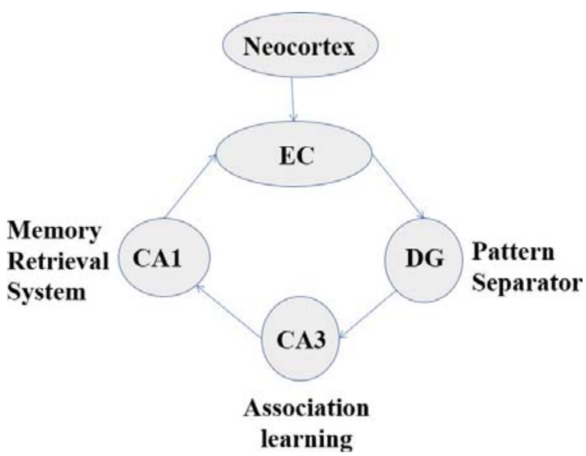



Figure 1: Sequential Circuit of Hippocampus.

As per research article [9], DG is divided into lamella's, where each lamellar contains both the excitatory and inhibitory neurons. This interneuron excited by and inhibit the granule cells of the same lamellar. Mossy cells of each lamellar excites by the granule neurons of the same lamellar.

These mossy cell neurons of DG excite the pyramidal neurons of the CA3 through mossy fiber input to CA3.Single mossy fibers spike train can cause the pyramidal neurons of the CA3 to fire. Second input to the CA3 comes from the performant path of EC. It is believed that this input is for

the recalling purpose to give incomplete pattern input to the CA3 pyramidal neurons. Each CA3 neuron takes very sparse input from the DG, also the connectivity between the DG and CA3 can be one to one.
We followed all these structural constraints which is needed to design a model for DG and CA3.
It is seen in various research that the neurons of the hippocampus use the STDP learning. This learning is a weight learning process which is explained in the implementation section of the paper.

Probability Based pattern separator:
In this research article they just proposed, that how the different parameters like (membrane constant, threshold, connectivity rate affects the separation efficiency of the DG. But, they did not describe how exactly the pattern separates or how the DG reduces the overlapped region between the patterns. And how CA3 stores and recalls. Which we included in our model [3].

Competitive Network based DG model:
According to ET Rolls, DG is a competitive network where the granule neurons compete with other neighbor neurons to spike, then after spike they inhibits the other neurons [4]. There is a problem with the model, that there is no parameter which decides that a neuron which fires for one pattern and will not fire for another similar pattern [8,11]. They just showed that a neuron which fires first will inhibit the other neighbor neurons, but it is not enough to understand how exactly it is happening. This shortcoming of the model we tried to solve and explained in well manner.

## II. Proposed Model

In proposed model (shown in figure 2), we described DG as a modulator which modulates the firing rate of the input neurons. Here DG is just like the filter which filters out the spikes coming fromtheuniqueinputneuron.Thespikesofthoseinputneuronswhichfiresinmorethanoneinput patterns less filters based on how many patterns it is present.

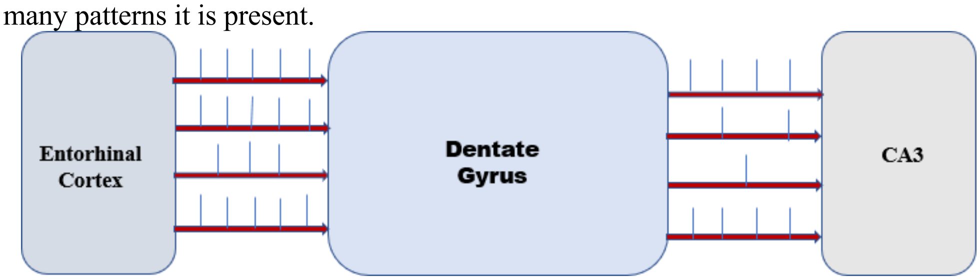



Figure 2: Proposed model for Hippocampus.

DG Model: As it is described in the literature section that the DG is having five times higher numberofneuronsthantheEC,andalsoitisdescribedtheDGisdividedintothelamellar(groups) whichishavingnon-overlappedneurons.Wefollowedthisstructure,soneuronsoftheDGdivided into the clusters, where each cluster can take the input from more than one input neuron, and also eachinputneuronofECcansendoutputtothemorethanclusters.So,everyclustercantakefixed number of input neurons, where each input neuron will be connected to each neuron of the same cluster.

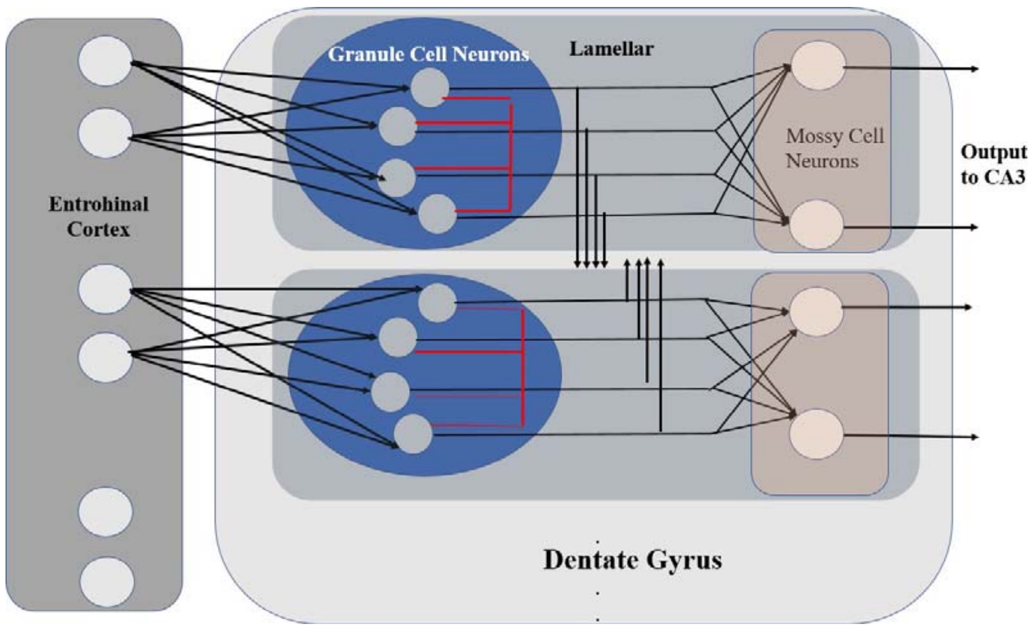



Figure 3: proposed model for Dentate Gyrus (DG).

Here, each cluster can have 2n neurons, where n is the number of the input neurons to each cluster. Each neuron of the clusters represents the all possible state corresponding to the input from the neurons of the EC.
Here every clusters activates the single state neuron corresponding to the input neuron this activated neuron deactivates the other neurons of the same cluster by the help of inhibitory connection.

Those states activate for the same pattern will start create associations with each other and with itself based on the STDP learning which is explained in detail in implementation section. Now we used spikes of these activated state neurons to inhibit the activation of the mossy cell neurons of the same cluster.
If the spike rate of these state granule cell neuron is high than they inhibit the mossy cell neurons higher and vice versa. This spike rate of the granule cell neurons depends on the association of with the granule cell neurons of others cluster and with itself. If this granule cell activates in more than one pattern then it will create more associations with the other repeated granule cell neurons and with itself which makes them fire at higher rate, as a result of it blocks the input pattern to encode (going towards CA3).

**CA3 Model:**
CA3 is a storage site which stores the filter patterns which is processed by the DG. Here it uses a single neuron layers where each neuron makes the recurrent connections with each other to perform associative learning, and to create associations between the neurons belongs other similar neuron.

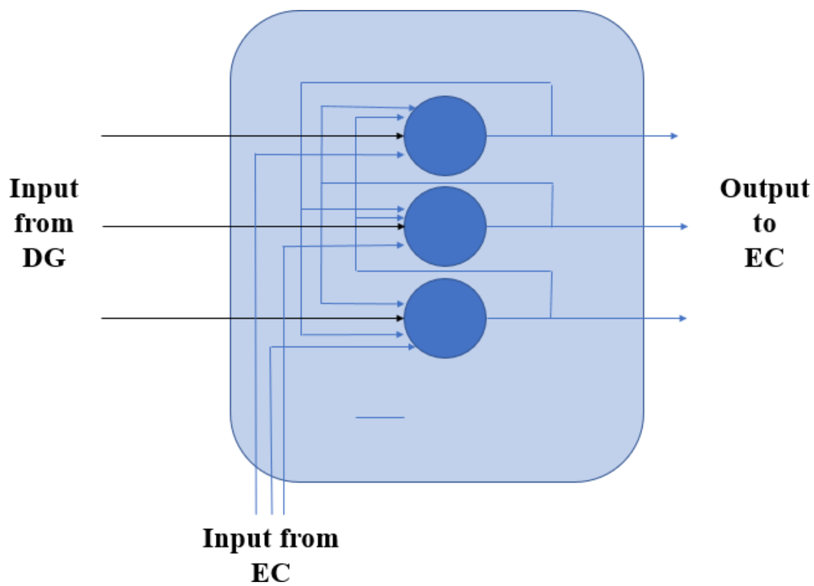



Figure 4: Proposed Model for CA3 region.

Here one to one mapping is used between the mossy cell neurons and the pyramidal cell neurons of the CA3. We can give incomplete pattern to the CA3 single layer neurons. Which will make activate the other neurons on basis of the associations of the neurons of the given incomplete pattern.

**Implementation Detail**

The whole proposed model is implemented by the help integrate and fire SNN model. Integrate and fire SNN is described in the below section.

**Integrate and Firemodel:**

We used fire and integrate version of SNN to implement our proposed model. In this type of SNN, a neuron is assumed to be a RC circuit which is having some potential (membrane potential) "U". This potential change with the time dependent input current (according to equation 1). The rate of change of potential is decided by the resistance and capacitance of the circuit called membrane constant which is denoted by () which is equals to the RC.

I(t) = I(r) + I(c)

I(t) = u(t) − urest

$R$

$+ C\,du$

$dt$

$\tau m *$

$du$

$dt = -[u(t) - urest] + R\,I(t)$

$u(t) = urest$
$+ (t) * R\,(1 - \exp(-$ t−t0 $\tau m)$ (1)

U(t) is the potential of a neuron (Given in eq. 1), which is a function of time dependent input current I(t), Resistance (R) and membrane constant ($\tau m$), and elapsed time (t). Where Urest is the resting potential of a neuron membrane.

**Weight Learning:**
In various research, it is found that the neurons of the hippocampus perform STDP Learning []. In this type of learning, the synaptic weight between any two neuron increases only if the post neuron gives spikes in response of the spikes of the pre-neuron. Here, if the gap between the timing of the spikes of both pre-neuron and the post neuron is small then the weight learning will be high and vice versa (learning is shown in figure). And if the post spikes come before of pre-neuron spike then weights go down.
To perform weight learning between any neuron and all its connected pre-neuron, we have used an energy function, where at the moment of spike, the neuron calculates the individual energy of all its connected pre-neuron to find the real contribution of each pre-neuron in its own spiking.
Mechanism is shown in figure 5, where spike timings of input and output spike of a neuron is given, where input spikes are coming from all its connected pre-neuron, as a result of all input spikes, post neuron generated an output spike. To perform weight learning of a post neuron with all its connected pre-neurons, at the moment of spike (at time t1) of post neuron, it calculated the energy E1, E2, E3 and E4 corresponding the spike raster (given in figure 5) of their connected pre- neurons by using the equation 2. At time t2, to calculate the energy of each pre neuron , post neuron considers only those spikes of their pre neurons which arrived after t1 and before t2.

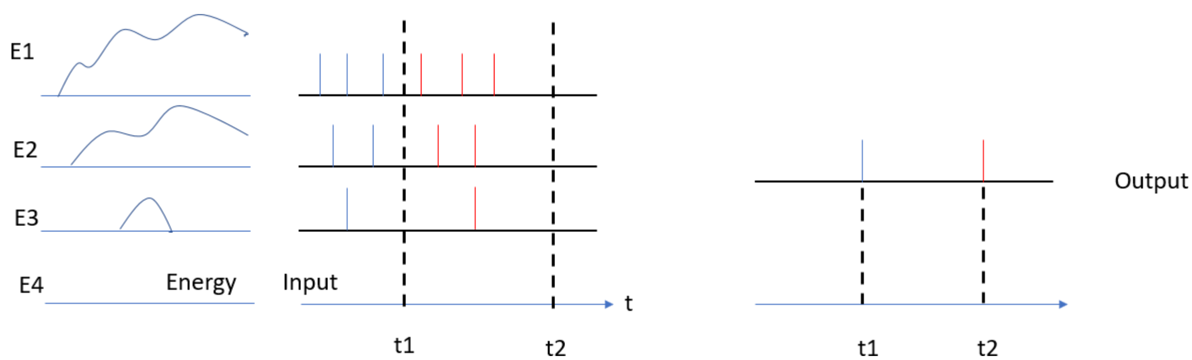



Figure 5: Weight Learning using Energy Function.

Current Required (t) = I * R Where I is the spike current constant, and R is the Resistance
t = (Et−1
− Current Required(t) ) ∗ (1 – e Δtτ ) (2)
Total Energy(t) = ∑i Et
Contribution (i) = $Et$ / Total Energy (3)
Wij = Wij + (e * contribution(i)) (4)
Where, Wij is the weight between the pre-neuron I h and post neuron j, e is the learning rate, and contribution(i) is the energy contributed by the spikes of pre-neuron i to the post neuron j.

Initially all weights are initialized with the 0.
In proposed model we use associative weight learning two times, first between the granule cell neurons of the DG of different clusters. Second, we used in between the pyramidal cell neurons of the CA3.
In associative weight learning, whenever a post neuron generates the spikes then it will see the spike raster of all other granule cell neurons of the different cluster from the time of last spike time of same neuron to the current spike time (shown in figure). To perform weight learning, Initially the excitatory weight between a granule cell neuron to the all other granule cell neuron are initializes with “0”.

**Post Synaptic Potential:**
Post synaptic potential of any neuron, generates by the incoming spikes of all its connected pre- neurons. To calculate PSP, each spike is considered as a constant amplitude current pulse of constant time. Then, we integrate the current pulse of all connected pre-neurons by simply adding the current which overlaps in time. For example: let suppose spike-current is having some constant value of 5 ampere, if three spikes from three different pre-neurons, come at the same time window then all these three spikes will add to gives 15 ampere currents to the post neuron. Voltage will increase according to the similar equation of integrate and fire model (Eq. 5).

**State Neurons:**
State neurons are those neurons which are representing the state corresponding to the input pattern generate at any cluster, e.g. if the input pattern 010 goes to any cluster then it will activate a neuron which are representing the state 2. To incorporate this functionality, we initialized the weights of all granule cell neurons of all clusters randomly from (-1,1). During representation of any input pattern, one of the state within the same cluster. Also, after generating the spike it will increase the weight corresponding to the activated input neuron and decreases the weight of the inactivated input neuron. So that a unique state can get corresponding to the unique input pattern.
Mossy cell Activation:
Activation of mossy cell decides by the input coming from the EC input neurons and the inhibitory input coming from the state (granule cell neuron) of the same cluster. Here the input neurons of EC are the same input neuron which are the input for the granule cell neurons of the cluster of the mossy cell neuron.
Experimental Detail:
In the experiment we used grid of black and white blocks where each grid is an input pattern of the white black block. This input pattern representing the pattern generate in the EC neurons, where black representing the corresponding EC neuron is activated and the neuron corresponding to the white denotes the inactivation of the neuron. Here in our experiment we used 3* 3 matrices of black white block grid (shown in figure). So here EC will have only nine neurons. Those are activated represents the black, and those are inactivated represents the white.

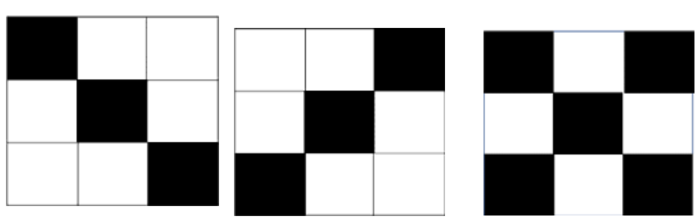


Figure 6: Input Grid Patterns.

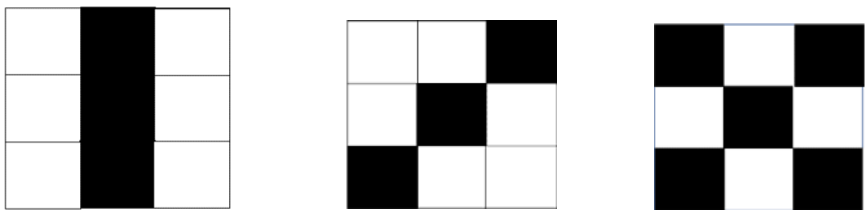
The output of those input neurons direct to the different cluster. Here we allowed only three neurons to go any cluster. For simplicity we allowed mapping of single input neuron to only single cluster (shown in figure).
Next, we have given these input patterns to the Model in the same sequence representing in the Figure. Here we allowed some overlapping between the patterns which is to reduce by the model.
Next, we have Given the incomplete pattern to the CA3 of the proposed model, and we get the corresponding output from the CA3 (shown in figure).

**Parameters:**
In proposed model, SNN is used, which makes the model much complicated to use. There are so many parameters which are need to consider for proper functioning of the model, like Spike current, Time constant, Threshold voltage and simulation time etc. These all parameters are discussed in detail below.
Time constant: It decides how precise is model, on increase of time constant the firing time of the two different neurons can come in the same time window and vice versa. In DG, state neurons it is required to be the low time constant so that the two-state neuron's will not come in the same window, and only one neuron will be the winner.
Spike-current: It is the current pulse corresponding to a spike. This current pulse is having some amplitude and pulse time (duration of pulse). This spike current decides the rate of change in voltage. If current is higher than the voltage will increase faster and vice versa. It is required to be that the gap between the spike-current coming to the DG neuron and its threshold voltage should be higher so that they will fire in the different window.
Simulation time: It is also a very important parameter, because it decides exactly how many spikes does it requires to make enough association to learn any pattern in single exposition, and how much time does it require to deactivate the activations of a neuron in the repeated exposition of any pattern.
Relation between the excitatory current and the inhibitory spike-current: Excitatory and inhibitory current are both parameters which decides the proper functioning of the mossy cell neuron. The mossy cell neuron is required to be activate in the first exposition of its corresponding input part of the pattern. But it is required to be deactivate during the second or more repeated exposition. Mossy cell takes excitatory spike from the entorhinal cortex neurons and inhibitory spikes from the granule cell neurons. The magnitude of inhibitory spike pulse must be low compared to excitatory spike, so that in very first exposition of any pattern, some inhibitory spikes will come which need not deactivate the mossy cell neurons.
In current experiment, for the neurons of the entorhinal cortex, membrane time constant is taken to be the value of, current is taken to be the value of 10 ampere, resistance is taken to be the value of 10ohm, simulation time is taken to be the value of 15ms, and threshold voltage is taken to be the value of 20 volt.
For the neurons of the granule cell neurons of the DG, input spike current is taken to be the value of 5 ampere, resistance is 10ohm, simulation time is similar for all neurons, and threshold is of 5volt.
For the neurons of the mossy cell neurons of the DG, input spike current is , resistance is 10 ohm.
, and threshold is of

## Results

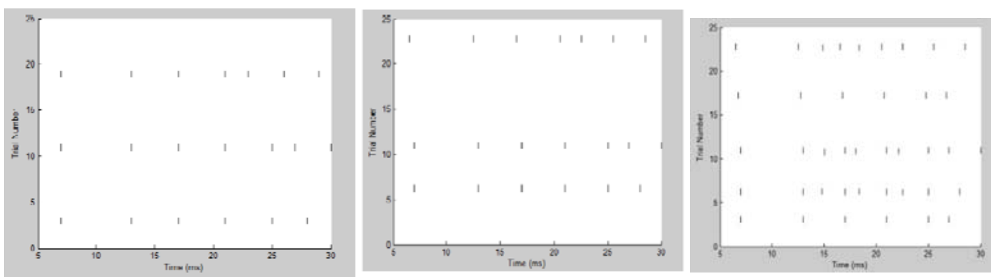
In this result section, we discussed the output results of granule and mossy cell neurons of DG (Output from DG) for different inputs, and also shown the output results of recalling from the hippocampus (pattern completion from the given incomplete pattern).
Activation of Granule and Mossy Cell Neurons:
Here we have given three different grid patterns of black white box as an input to DG, in a particular sequence one after another. It is provided that the color of some blocks is similar between the patterns to test the pattern separation efficiency of the model.

Results of the activation of Granule cell neuron on different pattern sequence is given below figure. In figure 7(I) input pattern sequence is given, and in figure 7(II) output of the activation of granule cell neurons corresponding to the input pattern sequence.



(a) (b) (c)

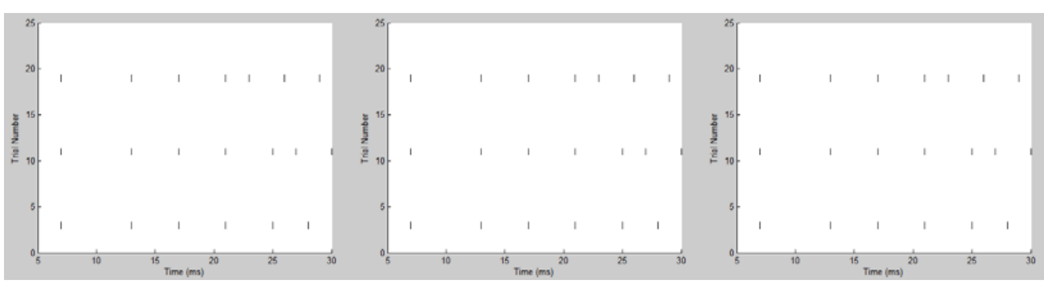
Figure 7 (i) : Input pattern sequence a, b, c.



(a) (b) (c)

Figure 7 (ii): Firing pattern sequence of granule cell neurons corresponding to the above input pattern sequence to the entorhinal cortex.

As we can see clearly in the results of the granule cell activations, that the neuron no is common in both the pattern a and b, because of some similarity in both patterns. During the input pattern b the activation rate of neuron is increased because of high associative weights with itself and other repeated co active neurons.



(a) (b) (c)

Figure 7: (iii) firing pattern sequence of mossy cell neurons corresponding to the above input pattern sequence to entorhinal cortex.

As we can see clearly in figure 7(iii), the mossy cell neurons which are corresponding to the repeated part of the pattern become deactivated or decreased its activation, because of the increased firing rate of the corresponding granule cell neurons.

**Recalling from Incomplete Pattern:**

According to indexing theory of hippocampus, it stores the different events as an index. Which the hippocampus uses to recall whole event from the incoming partial input cue.

Like this, hippocampus model store different patterns (events), which it can recall from the input cue (incomplete pattern). According to the research, it is found, for recalling purpose entorhinal cortex gives incomplete pattern directly to the CA3 region. As a result of this cue, CA3 recalls the other constituents of the pattern (recall whole pattern).

We have given some incomplete patterns to CA3 (cue). Their cues with their corresponding output patterns are shown in given figure below.

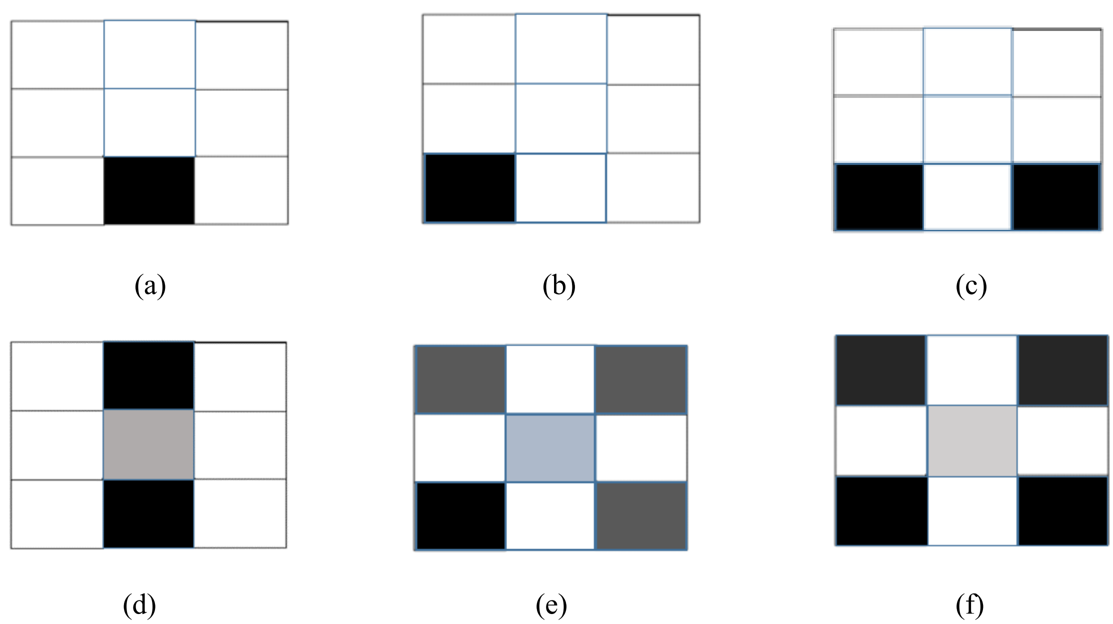



**Figure 8:** Input patterns and their corresponding recalled patterns a, b, c are the input patterns and d,e,f are their corresponding output patterns.

## Conclusion and Future Work

A firing-rate based pattern separator is used to model the DG region of hippocampus. We have stored several overlapped patterns and successfully retrieved from the input cue. Model is still lacking to learn the sequence of patterns, which we will try to remove by using theta wave generator in the next version of the model. In future, we will try to incorporate the proposed model in grid and place cell processing.

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